Livestock Science 121 (2009) 281–287

Contents lists available at ScienceDirect

Livestock Science

journal homepage: www.elsevier.com/locate/livsci

Control charts applied to simulated sow herd datasets

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ARTICLE INFO

Article history:
Received 29 June 2007
Received in revised form 19 May 2008
Accepted 27 June 2008

Keywords:
Statistical process control
EWMA
CUSUM
Pig production

ABSTRACT

Statistical control charts were used to detect process change in pig production. Two charts were tested to detect small deviations in production processes: the cumulative sum (CUSUM) control chart and the exponentially weighted moving average (EWMA) control chart. A Monte-Carlo simulation was used for developing an optimal design of the EWMA and the CUSUM charts. The traits piglets born in total and the return to oestrus rate were considered. Over a given time period, small shifts were purposely implemented to test the performance of the charts. The average time to signal (ATS) and false positive rate (FPR) were taken as classification parameters to evaluate the performance of the charts. All shifts in the number of piglets born in total were detected with CUSUM and EWMA control charts. The trait piglets born in total showed an ATS ranging from 1.3 (FPR = 33.5%) to 6.8 weeks (FPR = 1.2%) using the CUSUM chart. The EWMA chart presented an ATS which ranged between 2.0 (FPR = 14.9%) and 6.3 (FPR = 1.9%) weeks. The application of the CUSUM to the return to oestrus rate resulted in an ATS of 2.6 (FPR = 38.3%) to 15.6 weeks (FPR = 3.0%) and the EWMA chart produced a signal between 4.1 (FPR = 14.5%) and 16.4 weeks (FPR = 1.4%). Both charts appear to be useful tools for tracking commercial swine farm processes and detecting emerging change in process performance.

1. Introduction

The total number of swine breeding farms in Germany decreased from 77,000 in 1994 to 34,000 in 2004 (ZMP, 2005); however, the number of sows per farm increased. In 1994, 40% reached herd sizes of 100 or more sows. In 2004, the number of farms that kept sow herds larger than 100 sows reached 68%. Growing sow herd sizes and narrowed margins are the main characteristics of modern pig production. Therefore, the need for effective management information systems is becoming more important with increasing demand on the management skills of the farmer. Information technology enables the farmer to record and analyse farm data. To benefit from the huge amount of documented data, it is important to develop supporting computer algorithms, which can be used to detect emerging weakness as well as strengths in production processes. There are currently no specific statistical process control computer tools being used in swine production for tracing deviations from the process mean. Statistical process control charts are well-known tools for quality control in industrial processes, but in the analysis of agricultural datasets, only a few investigations have been made using this technique. De Vries and Conlin (2003, 2005) applied CUSUM (cumulative sum) control charts to detect oestrus in dairy cows. The authors mentioned that changes were detected soon enough to be potentially useful in dairy management. Pleasants et al. (1998) applied CUSUM to monitor effects on ultimate muscle pH in Angus and Hereford steers. In the latest study, Madsen and Kristensen (2005) monitored the condition of young pigs via their drinking behaviour with the CUSUM.

Walter A. Shewhart proposed the first theory of control charts. In its original form, the control chart is a simple time plot of an order of subgroup statistics, called Shewhart Chart. The Shewhart control chart uses the information of the last plotted observation, ignoring any information given by the entire sequence of the foregoing observations Statistical control charts can be used as a tool for detecting the presence of possible assignable causes of variation that might be

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doi:10.1016/j.livsci.2008.06.025

hidden in the variation due to common causes of variation. A process that is operating with only common causes of variation is said to be in statistical control. A process that is operating in the presence of assignable causes is said to be out-of-control (Montgomery, 1997) and investigation and corrective action are required depending on their impact on total economic farm performance.

This paper presents an approach for computer-based farm analysis, to support the decision-making of the farmer. The aim was to develop a method enabling the farm manager to quickly detect with statistical certainty emerging process changes in swine production. To gain more insight into the optimal design of the CUSUM as well as the EWMA (exponentially weighted moving average) chart in agriculture production processes without any side-effects, a simulation study was performed.

2. Materials and methods

2.1. Methods

A control chart consists of a centre line that represents the average value or the target specification of the observed variable. Two other horizontal lines called the lower and upper control limits are shown in the chart (Fig. 1). Based on previous observations, it is possible to set the limits to determine the probability that subsequent observations fall within these limits if the process is within statistical control. A data point outside the control limits is called a signal indicating there has been a shift of the production process and that the process is out-of-control. An out-of-control signal indicates that more variation is present than can be assigned to the effect of common causes of variation. Corrective action is required to restore or improve the process.

There are two effective charts that may be used when small deviations are of interest: the cumulative sum (CUSUM) control chart and the exponentially weighted moving average (EWMA) control chart, which were presented in this study.

2.1.1. CUSUM charts

The CUSUM chart, originally developed by Page (1954), incorporates all information in the sequence of sample values and plots the cumulative sums of the deviations from a target value using samples from all prior observations. The CUSUM control chart has a rather long memory due to the fact that it uses a non-weighted sum of all prior observations (Fig. 2).

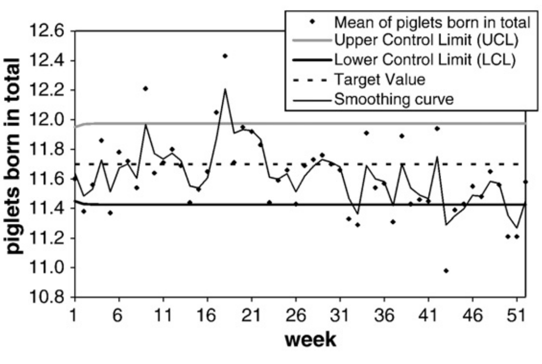

Fig. 1. Illustration of a control chart (EWMA chart).

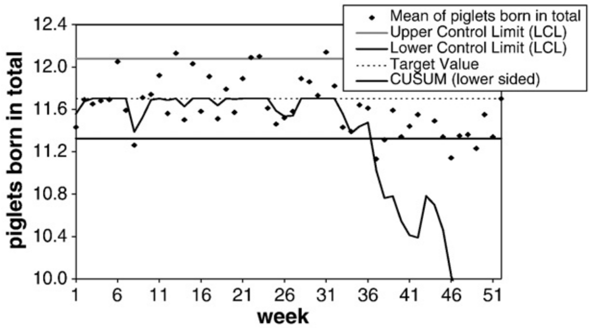

Fig. 2. Illustration of a lower-sided CUSUM control chart.

This CUSUM method differentiates between upward and downward drifts, therefore a calculation of the upward and downward cumulative sum of the observations is performed.

They are computed as follows:

$$C_i^+ = max\left[0, x_i - (\mu_0 + k) + C_{i-1}^+\right]$$

$$C_i^- = max\left[0, \mu_i - k) - x_i + C_{i-1}^-\right].$$

The variable x_i is independently distributed as $x_i \sim N(\mu_0, \sigma^2)$ if the process is within control. C_i^+ and C_i^- are called one-sided upper and lower CUSUM, respectively. Starting values for upper (C_i^+) and lower (C_i^-) CUSUM are 0. The two-sided CUSUM accumulates deviations above μ_0 to the upper CUSUM (C_i^+) and below μ_0 to the lower CUSUM (C_i^-).

The CUSUM chart can be adjusted with the reference value k. It is chosen for an optimal response to a shift of a specified size. Montgomery (1997) and Hawkins and Olwell (1998) recommend that k should be chosen relative to the size of the shift that is to be detected. They recommend a k-value that is half the size of the shift that is to be detected. Low k-values effect a high sensitivity, higher values result in lower reaction of the chart.

The upper (UCL) and lower control limit (LCL) are determined by the h-value, also called the decision interval. This value expresses the factor of σ_0 defining the distance between μ_0 and the limits UCL and LCL, respectively.

$$\text{UCL} = h^*\sigma$$

$$\text{LCL} = -h^*\sigma$$

An alarm signal is given when either C_i^+ or C_i^- exceeds the UCL or the LCL respectively. For more details, see Page (1961), Crosier (1986), Hawkins and Olwell (1998).

2.1.2. EWMA charts

Since the EWMA control chart was first introduced by Roberts (1959), a variety of methods have been developed to detect shifts in the process mean. Like the CUSUM control chart, the EWMA utilises all previous observations but in EWMA control charts the process is monitored using a weighted moving average of the foregoing observations. The weights decline exponentially depending on the smoothing constant λ with increasing time distance between historical and actual value. The EWMA control chart smoothes out the effect of single disturbances, and shows the behaviour of the level of the data.

The value of the EWMA statistic at time *i*, which is denoted by z_i is defined as:

$$z_i = \lambda x_i + (1-\lambda) z_{i-1}$$

where λ is a constant satisfying $\lambda \in (0,1)$. The information to compute z_i is present in z_{i-1}. If $\lambda \rightarrow 1$, then $z_i \rightarrow x_i$ and the EWMA control chart puts all of its weight on the most recent observation and the EWMA chart behaves like a Shewhart chart if $\lambda \rightarrow 0$, the most recent observation has a very small weight and the weight that is attached to the older observations only slightly declines with age of the observations. If the observations x_i are independent random variables with variance σ_0^2, the variance of z is:

$$\sigma_z^2 = \sigma^2 \left[\frac{\lambda}{2-\lambda}\right] \left[1-(1-\lambda)^{2i}\right]$$

UCL and LCL are derived as follows.

$$\mathrm{LCL} = \mu_0 - L\sigma \sqrt{\left(\frac{\lambda}{2-\lambda}\right) \left[1-(1-\lambda)^{2i}\right]}$$

$$\mathrm{UCL} = \mu_0 + L\sigma \sqrt{\left(\frac{\lambda}{2-\lambda}\right) \left[1-(1-\lambda)^{2i}\right]}$$

The upper (UCL) and lower control limits (LCL) are determined by λ, the overall mean (μ_0) and standard deviation (σ). The *L*-value has the greatest impact on distance between μ and the limits.

If the realisation of z_i is smaller than LCL or greater than UCL, the EWMA chart generates an out-of-control signal at time *i*. For more details, see Crowder (1987) and Lucas and Saccucci (1990).

2.1.3. Evaluation of the classification

There are two different types of errors that can be made by a statistical control chart. First, there is the Type Error (false positive), which occurs when the chart gives a signal, but the process is in control. Second, there is the Type Error (false negative), implying a risk of an observation falling within the control limits when the process is in actual fact out-of-control. Crowder (1987) and Lucas and Saccucci (1990) evaluated the average run length (ARL) as a performance criterion of EWMA charts. The ARL is the number of points that must be plotted before a point indicates an out-of-control condition. For detailed information, see Wieringa (1999), Goel and Wu (1971), Brook and Evans (1972) and Woodall (1983). In the present study, the parameter *in control average time to signal* (ATS_0) was derived analogous to the average run length (ARL_0). ATS_0 should be high to minimise the Type I errors. This type of error is also classified by the *false positive rate* (FPR), that is the percentage of false positive alerts in relation to all in control values. The choice of a high ATS_0 results in a higher number of Type II errors; due to the setting of the constants, the control limits would be far apart from the target specification and the chance of a real shift in process staying undetected would increase.

The third parameter used in this study is the *average time to signal* (ATS), which characterises the mean time to detect a shift in process.

The ATS_0 of the EWMA chart depends on the smoothing constant λ and on the width of the control limits, which is determined by *L*. The CUSUM chart has two constants, the reference value *k* and the decision interval *h*, which defines the control limits. These constants need to be chosen with care. Therefore in the present study the first step was to set up a Monte-Carlo simulation to find out about the in control ATS, to obtain the appropriate design constants for both charts. Based on these results, the second part of the simulation, the generation of the data with downward shifts, was performed.

2.2. Generating data by simulation

To obtain the optimal design for the EWMA and the CUSUM charts in pig production, a Monte-Carlo simulation was performed using the SAS statistical software (SAS, 2004).

2.2.1. Simulated traits

The most important trait in pig production is the number of piglets weaned per sow per year. This is not only affected by the litter size but also the number of litters per sow per year (Fig. 3).

The litter size traits were simulated for a sow herd at a medium production level provided by the yearly report of the extension service from Northern Germany (Kirchner et al., 2004). Piglets born in total (nbt) were generated from a normal distribution ($\mu_0 = 11.7$, $\sigma_0 = 2.5$); the piglets stillborn (nsb) per litter were sampled from a Poisson distribution. Hence, piglets born alive (nba) per litter were the difference between nbt and nsb. The pre-weaning mortality (%) was simulated by drawing a random number from the Poisson

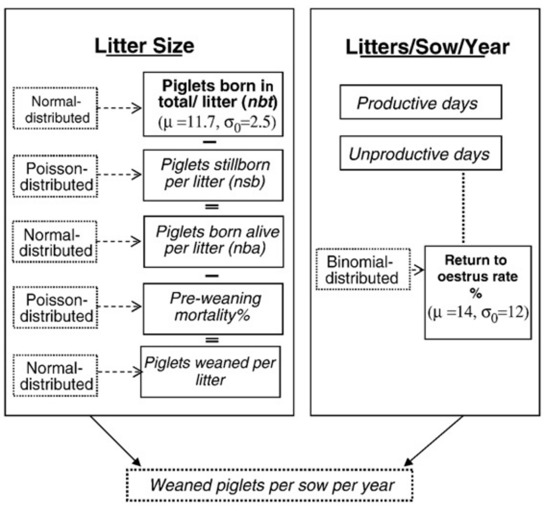

Fig. 3. Influences that affect the number of piglets weaned per sow and year. The traits printed in bold are discussed in the present paper.

distribution and subtracting the result from the number of piglets born alive. The pre-weaning mortality rate was 10% following the investigation by Kirchner et al. (2004).

The number of unproductive days influences the number of litters per sow and year and therefore the breeding herd efficiency. In this study, the return to oestrus rate was considered to represent one important factor influencing the number of litters per sow and year. Return to oestrus rate (roe) was binary distributed with a mean of 14% and a standard deviation of 35%.

The traits number of piglets born in total (nbt) and return to oestrus rate (roe) are discussed in the present paper.

2.2.2. Generating the in control ATS

The different traits were generated assuming 100 litters per week and repeated 100,000 times. No shifts were implemented. Based on the simulated 100 values, weekly means were calculated and used to determine the charts. For the evaluation of $ATS_{0,}$ the number of iterations was divided by the number of false positive alerts.

With the ATS_0, it was possible to roughly design the optimal value of the two constants h and k of the CUSUM control chart as well as L and λ of the EWMA control chart.

The ATS_0 of the nbt for the EWMA chart is presented in Fig. 4 as an example.

The size of ATS_0 chart increased with rising L-values, e.g. an $L=2$ resulted in an ATS_0 of 163 to 45 weeks. Choosing a smaller L-value ($L=1$), ATS_0 ranged from 31 to 7 weeks. Low λ-values resulted in exponentially higher $ATS_{0.}$ The ATS_0 thus needs to be as sufficiently long as the ATS to detect a shift in process should be short. A high ATS_0 will result in fewer Type I errors but the number of Type II errors will increase. A low ATS_0 results in a higher chance of Type I errors.

The size of ATS_0 for the EWMA chart increased with rising L-values. for example an L-value of 2 resulted in ATS_0 from 163 to 45 weeks. Choosing a smaller L-value like 1, ATS_0 ranged from 31 to 7 weeks arise. Distance between curves are higher if the standard of L is already high ($L>1.5$). Low λ-values resulted in exponentially higher ATS_0 (Fig. 4).

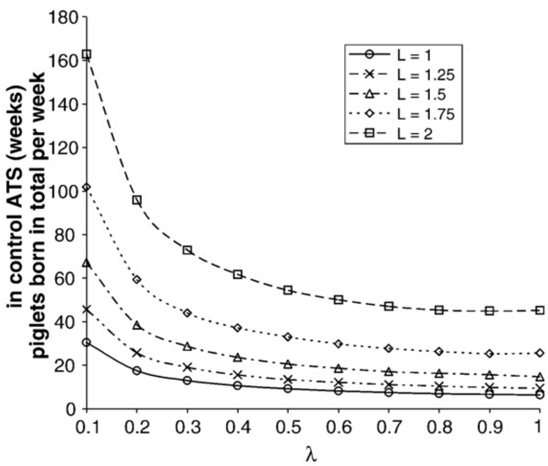

Fig. 4. In-control average time to signal (ATS_0) of piglets born in total per week, depending on the smoothing constant λ and varying L-values.

Table 1
In-control average time to signal (ATS_0), average time to signal (ATS) and false positive rate (FPR) for the number of piglets born in total (nbt) depending on settings of constants (h- and k-values) and different shifts using CUSUM

h	k	ATS_0 (weeks) [a]	FPR (%)	ATS (weeks) Shift $=0.1\ \sigma_0$	ATS (weeks) Shift $=0.2\ \sigma_0$
1.0	0.25	2.7	33.5	2.1	1.3
1.0	0.50	5.3	18.7	2.5	1.3
1.0	0.75	11.7	8.4	3.8	1.6
1.5	0.25	3.5	24.8	2.7	1.4
1.5	0.50	8.7	10.6	3.4	1.6
1.5	0.75	25.8	3.2	5.4	2.0
2.0	0.25	4.5	17.8	3.2	1.5
2.0	0.50	14.4	6.1	4.2	1.9
2.0	0.75	56.4	1.2	6.8	2.4

[a] Simulation part I; without any shift.

The ATS_0 needs to be sufficiently long as the ATS to detect a shift in process should be short. A high ATS_0 results in fewer Type I errors but the number of Type II errors will be high. A low ATS_0 results in a higher chance of Type I errors.

Comparable calculations of ATS_0 were carried out for the CUSUM chart resulted in higher ATS_0 with increasing h- and k-values. A low k-value ($k=0.25$) combined with varying h-values resulted in low ATS_0, while the length of ATS_0 slightly increased with the choice of a higher h-value (number of piglets born in total; $h=1 \rightarrow ATS_0=$ 2.7 weeks, $h=2 \rightarrow ATS_0=$ 4.5 weeks). A high k-value (0.75) resulted in higher ATS_0 e.g. for piglets born in total, varying from 11.7 ($h=1$) to 56.4 ($h=2$) weeks.

Based on these results a range of values of the constants was chosen in order to evaluate the performance of the charts.

2.2.3. Implementation of shifts

In the second part of the simulation, 100 litters per week were generated. In this simulation, the time period was 52 weeks to represent the production year. For the traits that represented the litter size, a negative shift of 0.1 σ and 0.2 σ, respectively was implemented from week 33 till week 52. Return to oestrus rate was set 2% higher (14%→16%) and 4% higher (14%→18%), the standard deviation of the binomial distribution was adjusted. Simulations were replicated 100 times.

3. Results

3.1. Number of piglets born in total (nbt)

The two implemented shifts (0.1 σ_0 and 0.2 σ_0, respectively) were always detected which led to a sensitivity of 100%; however, ATS and FPR differed depending on the settings of the constants.

The higher shift in the mean led to better classification results. The mean time until detection of the shifts was reduced to about half the time, when the size of the shift that was to be detected increased from 0.1 σ_0 to 0.2 σ_0.

An increasing h-value (from 1 to 2, $k=0.5$, shift $=0.1\ \sigma_0$) led to a decrease in FPR, from 18.7% to 6.1%, but simultaneously, to an increase in ATS, from 2.5 to 4.2 weeks (Table 1). A smaller k-value made the CUSUM chart react more quickly, showing a short ATS and a high FPR. The size of the k-value had a considerable effect on the response of the CUSUM chart. The choice of a low k-value resulted in a low ATS_0, with a higher k-value the ATS_0 was higher.

Table 2
In-control average time to signal (ATS_0), average time to signal (ATS) and false positive rate (FPR) for the number of piglets born in total (nbt) depending on settings of constants (*L*- and λ-values) and different shifts using EWMA

L	λ	ATS_0 (weeks)[a]	FPR (%)	ATS (weeks)	ATS (weeks)
				Shift = 0.1 σ_0	Shift = 0.2 σ_0
1.0	0.2	17.8	6.8	3.5	1.8
1.0	0.4	10.7	10.1	2.6	1.4
1.0	0.6	8.2	12.7	2.3	1.5
1.0	0.8	7.0	14.9	2.0	1.2
1.5	0.2	38.5	2.9	4.3	2.2
1.5	0.4	23.6	4.3	3.8	1.7
1.5	0.6	18.6	5.4	3.5	1.5
1.5	0.8	16.2	6.3	3.3	1.4
2.0	0.2	95.9	1.0	5.8	2.6
2.0	0.4	61.7	1.7	5.4	2.2
2.0	0.6	50.1	1.9	5.6	2.0
2.0	0.8	45.3	2.0	6.3	1.9

[a] Simulation part I; without any shift.

The EWMA (λ = 0.2) showed a decrease in FPR from 6.8% to 1.0% if *L* increased from 1 to 2 as a result that LCL had a greater distance to the target value (Table 2). ATS ranged from 3.5 ($L = 1$) to 5.8 ($L = 2$) weeks due to the fact that the probability of an observation falling beyond the control limits is reduced with higher *L*-values.

By the choice of weighting factor λ, the EWMA chart can be made sensitive to a small or gradual drift in the process. Hence, a higher λ led to lower ATS but the number of false positive alerts increased significantly. With a shift in the mean of 0.1 σ_0, the ATS of nbt was determined to be between 2.0 and 6.3 weeks. If the shift in the mean rose to 0.2 σ_0, ATS declined to values between 1.2 and 2.6 weeks.

3.2. Return to oestrus rate (roe)

The behaviour of the charts using the weekly means of the return to oestrus rate cannot be compared to the operational behaviour of the charts when looking at nbt. The weekly means varied more distinctly than the shifts that were implemented, therefore the chance of not detecting the implemented shift was given (Type II Error). If the shift that was to be detected was low (2% up), the ATS was longer than the calculated ATS_0 (Table 3). With higher *h*-values and increasing *k*-values, the sensitivity of the CUSUM chart decreased e.g. an *h*-value of 2.0 combined with a *k*-value of 0.75 resulted in a sensitivity of only 39%. The sensitivity represents the proportion of true positive alerts to all alerts and is also called the true positive rate. In this case, it was important to calculate the ATS including the sensitivity because not all shifts were detected.

The ATSc was calculated as follows:

$$\mathrm{ATSc} = (ATS^{*}\mathrm{Sensitivity} + (100 - Sensitivity)^{*}20\,\mathrm{weeks})/100$$

With the use of ATSc, the sensitivity of the chart was taken into account to calculate the time until a signal occurred. This was essential to avoid the ATS being too low given that only the detected shifts would have contributed information to calculate the ATS. If the sensitivity was 100% e.g. all shifts were detected, then ATSc = ATS. The sensitivity of the return to oestrus rate decreased with higher *h*- and *k*-values (Table 3).

Table 3
In-control average time to signal (ATS_0), calculated average time to signal (ATSc), sensitivity (%) and false positive rate (FPR) for return to oestrus rate (roe) % depending on settings of constants (*k* and *h*) and different shifts using CUSUM

h	*k*	ATS_0 (weeks)[a]	FPR (%)	ATSc (weeks)	Sensitivity	ATSc (weeks)	Sensitivity
				Shift 2% up		Shift 4% up	
1.0	0.25	2.1	38.3	3.0	98	2.6	100
1.0	0.50	4.3	20.2	5.1	96	3.8	100
1.0	0.75	8.6	10.5	8.8	87	6.6	92
1.5	0.25	2.7	29.2	4.6	97	3.6	98
1.5	0.50	6.5	13.1	8.7	85	6.2	95
1.5	0.75	14.6	5.8	12.0	71	9.8	80
2.0	0.25	3.3	21.3	6.6	91	4.7	98
2.0	0.50	9.9	8.1	12.0	65	9.4	84
2.0	0.75	28.5	3.0	15.6	39	13.4	57

[a] Simulation part I; without any shift.

The EWMA chart applied to the return to oestrus rate showed FPR that were similar to the FPR of the nbt. The ATS_0 was low therefore the chance of a Type I error was higher. The ATSc (shift 2%) ranged from 5.3 to 16.4 weeks. If the shift was higher (4%), the ATSc ranged from 4.1 with a setting of a low *L*-value ($L = 1$) and a high λ (λ = 0.8) to 13.6 ($L = 2$, λ = 0.2) weeks. The sensitivity of the EWMA chart decreased with increasing *L*-values and increasing λ-values (Table 4). A sensitivity of 100% was only reached with a low shift (2%) and a setting of $L = 1$ with the smoothing constant set at a high level (λ = 0.6 and λ = 0.8).

4. Discussion

Control charts are widely used instruments for statistical control in industrial processes but data that arises in industrial processes cannot be compared with the biological data used in the present study. Therefore, a simulation study was useful to find the best settings of the constants for, in this case, sow production data, with the aid of the classification

Table 4
In-control average time to signal (ATS_0), calculated average time to signal (ATSc), Sensitivity (%) and false positive rate (FPR) for return to oestrus rate % depending on settings of constants (λ and *L*) and different shifts using EWMA

L	λ	ATS_0 (weeks)[a]	FPR (%)	ATSc (weeks)	Sensitivity	ATSc (weeks)	Sensitivity
				Shift 2% up		Shift 4% up	
1.0	0.2	13.3	6.6	7.5	86	7.2	92
1.0	0.4	8.5	10.0	6.6	93	5.4	98
1.0	0.6	6.8	12.7	5.3	97	4.3	100
1.0	0.8	5.9	14.5	4.6	99	4.1	100
1.5	0.2	26.2	3.2	13.0	67	10.2	86
1.5	0.4	16.3	4.9	10.2	81	7.9	89
1.5	0.6	13.1	6.5	9.3	83	6.6	94
1.5	0.8	11.3	7.9	7.4	91	5.9	95
2.0	0.2	53.3	1.4	16.4	43	13.6	67
2.0	0.4	35.6	2.2	14.9	52	12.1	74
2.0	0.6	28.8	3.0	14.5	55	11.9	73
2.0	0.8	25.3	3.3	13.3	63	10.4	75

[a] Simulation part I; without any shift.

parameters ATS_0, ATS (ATSc respectively) and FPR. In general, industrial processes produce large amounts of data with low variation and the sample sizes differ from the ones achieved when swine farm data is observed. Biological processes show a greater variation and the number of available observations is often lower. In the current study, weekly means were used to analyse the statistical process in sow farm data. The lack of sufficient data to use statistical methods creates a problem. Applying control charts to weekly means, the herd sizes should be large enough to offer a sufficient amount of data that can be examined. If the number of observations per week is too small an extension of the time interval is recommended.

Decisive for the performance of both CUSUM and EWMA charts is the setting of the constants. The constants of the charts need to be set according to the shift which is to be detected and to identify possible problems as quickly as possible. It is difficult to choose the design constants L and λ of the EWMA Chart and h and k of the CUSUM chart. With lower λ ($0.05 \leq \lambda \leq 0.25$), smaller shifts can be detected by the EWMA chart. A high λ will detect larger shifts faster, if $\lambda = 1$, the EWMA chart behaves like the Shewhart chart. The choice of λ is more important if small shifts are to be found. Differences between ATS for different λ became smaller with higher shifts.

If ATS is low, more false positive alerts will occur, but the chance of detecting real shifts earlier increases. The classification constants L (EWMA) and h (CUSUM) behaved in a similar way: a high value resulted in broader control limits, which caused longer ATS and smaller FPR.

General recommendations on how to set up the CUSUM or the EWMA chart are hard to provide. The simulation results showed that the choice of a low k-value (0.25) resulted in a very early detection of the shift. At the same time, the FPR were very high and the ATS_0 were low. A k-value of between 0.5 and 0.75 is recommended to prevent the extent of false alerts. The h may be set between 1 and 2 and the differences in the charting behaviour were mostly influenced by the k-value. For the EWMA chart, a λ of between 0.4 and 0.6 combined with an L-value of 1.5 worked well. The setting of the constants is always a trade-off between an early detection of changes in process and an acceptance of possible false alarms.

Time series data often showed serial correlations. If serial-correlated data are monitored, the control limits need to be adjusted. Wieringa (1999) mentioned that the CUSUM chart is even more affected by serial correlation than the EWMA chart. Negative autocorrelation results in a certain insensitivity of the control chart, positive autocorrelation will result in many false alarms. Wieringa (1999) proposed several methods for accounting serial correlation in control charts, e.g. the EWMA chart which can be modified by widening the control limits to account for the increase in variance.

Hawkins and Olwell (1998) mentioned that false positive alarms are undesirable. They cause unnecessary use of time and energy as well as disrupt operations while searching for non-existent causes. This statement might be true for most industrial processes. In manufacturing, a false positive alert is serious due to potentially considerable costs which might arise as a result of stopping the production process to investigate a non-existent problem. When dealing with sow farm data, it is much more important to detect every actual shift as quickly as possible. For the farm manager, an amount of effort, time and money is needed to look at the production process due to a false positive alert but the production process is not stopped when an alarm is given. The CUSUM as well as the EWMA chart may be adjusted to the special needs of the farm manager. When choosing the setting constants to set control limits that are wider than the target, both charts will react with lower ATS but, at the same time, the number of false alerts will also be reduced.

5. Conclusions

With optimal design, both charts were useful tools to detect process change in commercial swine farming. After an alert occurs, troubleshooting should be carried out to eliminate the problem. To set up the charts and detect shifts in data based on weekly means, lower ATS_0 than recommended in the literature should be used.

Both the EWMA and CUSUM charts enable a clear graphical presentation of the results. The classification performance is comparable. The presentation of the EWMA chart may be easier to understand, because actual values are assigned in contrast to CUSUM, which works with deviations. An advantage of CUSUM is the possibility to differentiate between calculating the positive and negative deviations. Modern computer technology enables the implementation of control charts in online production monitoring. Further, analysis of the relevant (out-of-control) deviations should examine the underlying causes to improve farm performance.

Control charts seem to be useful tools to trace shifts and deviations in commercial swine farming. To test the performance of the CUSUM and the EWMA charts, both charts should be applied to actual sow farm datasets.

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